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Efficient Task Realizations in Networked Production Infrastructures

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Abstract

As Industry 4.0 infrastructures are seen as highly evolutionary environment with volatile, and time-dependent workloads for analytical tasks, particularly the optimal dimensioning of IT hardware is a challenge for decision makers because the digital processing of these tasks can be decoupled from their physical place of origin. Flexible architecture models to allocate tasks efficiently with regard to multi-facet aspects and a predefined set of local systems and external cloud services have been proven in small example scenarios. This paper provides a benchmark of existing task realization strategies, composed of (1) task distribution and (2) task prioritization in a real-world scenario simulation. It identifies heuristics as superior strategies.

Keywords

Industry 4.0; CPS; Decentral Decision Making; Industrial Analytics; Case Study

1. Introduction

Faced with an increase in the complexity of company IT infrastructures, such as an increasing number of networked machines and their heterogeneity in hardware and software [1], companies are often challenged with dimensioning capacities for processing of time-critical analytical tasks. Since companies aspire to realize tasks using the least resources as possible, new infrastructure trends emerged to cost-efficiently use existing resources: examples refer to Cloud-Computing, Edge-Computing, hardware outsourcing and adaptable enterprise architectures. Beside costs, as a trade-off, further criteria need to be considered, so that e.g. jobs are realized in time. Assuming to have internal and external processing systems with different sets of rights per layer and capabilities, generic multilayer hardware infrastructure models seem to be promising ways to achieve scalable and flexible infrastructures without maintaining oversized IT-infrastructures [2].

Given the many heterogeneous computing devices in modern production infrastructures, questions about the efficient use of Industry 4.0 resources further complicate decisions about the organization of analytical infrastructures. For this, a variety of task distribution approaches within networked infrastructures have evolved, each exhibiting characteristic advantages and disadvantages [3]. Under these, one can find a tendency for decentralized, heuristic approaches [2], since these simplify the strategy determination.

Former studies approached the evaluation based on hypothetical data [2], which seems reasonable as a start. To confirm validity of research results established, this current contribution is based on a real-world practical case study and thereby expands the collection of small and theoretical benchmarks considered so far. By the use of a realistic example containing numerous systems and public cloud services, working on real system data satisfies complexity of Industry 4.0 production. So, we aim to answer the following research question:

How can analytical tasks be efficiently distributed and processed within networked production infrastructures?

2. Theoretical Foundation

For the examination close to reality, this contribution considers different forms of analytical tasks, that are realized by various levels of computing infrastructures within the context cyber-physical production systems. The first subsection therefore describes theoretical terms and principles corresponding to the related literature. The second subsection then presents underlaying concepts, on which the contribution builds: the benchmark carried out considers a comparison of different task realization strategies as well as the new heuristic approach called NDM, and further the performance is measured by an adequate framework.

2.1 Related Literature

Cyber-Physical Production System. As a result of integrating cyber-physical systems (CPS) into production systems, more and more manufacturing components become connected. The combination of multiple cyber-physical systems within one common production setting can be referred to as Cyber-Physical Production System (CPPS) [4, 5]. Because of intelligent components being distributed within production environments, a cooperative planning can replace the traditional linear, hierarchical planning and control [6]. To realize the production process, a complex interplay of CPPS components is necessary similar to autonomous logistic systems (e.g. [7]). Therefore, each CPS interacts autonomously based on its decision strategies to realize a cooperative planning solution. These are considered as analytical tasks from hereon.

Computing Infrastructures. Different concepts exist to classify computing infrastructures of companies. While each company might have a unique infrastructure, common elements, structures and hierarchies can be identified. Issuing the distribution of tasks, a generic concept is desirable that firstly provides typical infrastructure levels, e.g. for differentiating the processing power, and secondly is able to specify levels dependent on the system's individual situation. In the following, a separation in three typical infrastructure levels is used [2, 8], by which computing systems are grouped into three levels (Table 1).

Table 1: Level Characterization

Level	*Description*	*Source*
CPS level	Computing resources being situated at the shop floor level. Subsumed as CPSs, they are able to sense their environment, process their perception in order to derive decisions, communicate with other CPS, and carry out decisions with the aid of actuators. Hence, they are attractive to carry out analytical tasks by themselves.	[4]
Local Cloud	Computing resources being interconnected by local or virtual networks within and across company sites [9]. These are typically more powerful than a single CPS [8] and therefore attractive to support CPS level systems for the realization of heavy analytical tasks.	[8], [9]
Public Cloud	Computing resources of external parties being rented for the heaviest computing tasks. Being integrated as service, they subsume highly scalable resources supplementing a company's infrastructure. Hence, they are attractive to quickly disburden the company in the realization of analytical tasks.	[10]

Industrial Analytics. Oriented to [11], analytical tasks of Industry 4.0 production systems can be categorized by eight task types being able to be processed in parallel [12]. These task types refer to Business Intelligence (BI) categories, such as reports, spontaneously instructed reports, drilldowns and alarms, as well as Business Analytics (BA) categories, such as statistical analyses, intra- and extrapolation, prediction models and scenario-based optimizations (increasing order). According to the assumption of Davenport and Harris, the effort of higher task types rises while resulting in higher competitive advantages.

2.2 Underlying Concepts

Efficient Task Realizations. Being faced with an architectural design, that provides various computing infrastructure layers for the realization of an analytical task, these differ in processing capability (supply), and task types requiring for individual processing capabilities for an analytical task, the optimal fit of demand and supply needs to be identified according to economic objectives to be identified as efficient.

The realization of an analytical task is operationalized by the following three: (1) the *analysis* of available tasks at any system being considered as origin, (2) the *transferring* of generated tasks based on the system's transfer strategy, this can be referred to as task distribution, and (3) the processing of arriving tasks based on a processing strategy, this can be referred to as task prioritization and assigns an order to arriving tasks [2]. While the transferring strategy e.g. can refer to heuristic strategies, processing strategies can refer to consumption sequence procedures, such as Last-In-First-Out (LIFO), First-In-First-Out (FIFO), Slowest-In-First-Out (SIFO) according to the collection of [2].

The New Decision Maxim (NDM). The NDM proposed by [2] serves as heuristic decision guideline for CPSs to decide at which system to process analytical tasks. It is so suitable to be a transferring strategy of tasks. Depending on the level where the decision is taken, different options exist. According to the current design of the generic architecture presented, three layers and four options can be identified. These are visualized in Table 2 and described thereafter.

Table 2: Task Allocation Options

Option / Level	*Vertical-up*	*Vertical-down*	*Horizontal*	*Local*
CPS level	X	-	X	X
Local cloud	X	X	X	X
Public Cloud	-	X	(X)	X

First, tasks can be processed locally, whereby the entity computes the results itself. Task can be distributed vertically. This includes the distribution to higher levels (upward distribution) or lower levels (downward distribution). Tasks can also be distributed to systems on the same level (horizontal distribution). Dependent on collaboration strategies of public cloud service providers, a horizontal distribution is not allowed, which is the reason for the (X) in Table 2.

NDM Configuration. While the NDM provides ability to conduct different criteria, we employ the same escalation prioritization as [2] in order to ensure comparability of benchmark results. By this, our contribution refers to the validation of the NDM approach in a realistic case study and performing on real data. So, Figure 1 presents the NDM configuration and clarifies the heuristically escalation strategy selection of an example system of the local cloud level.

Evaluation Criteria	Example Task	Escalation Prioritization: Local Proceccing	Vertical Upwards	Vertical Downwards	Horizontal Escalation
Task Effort	0.9	-0.5	0.9	-0.9	0.0
Divisibility	0.2	0.0	-0.6	0.4	0.6
Priority	0.5	0.15	0.8	-0.8	0.0
Current Load	0.8	-0.9	0.3	0.0	0.0
	Eval$_m$	-1.095	1.33	-1.13	0.12
	max(Eval$_m$)	3	1	4	2

Figure 1: New Decision Maxim Prioritization Example

The example task is characterized by a task effort of 0.9, a divisibility of 0.2, a priority of 0.5, and a current load of 0.8. Being masked by allocation options of Table 2 and weighted with regard to the evaluation prioritization of Figure 1, the best option is identified by the maxima. For the example task presented, the vertical upward escalation shows the highest value and therefore refers to the best solution in this case.

Performance Evaluation Framework. In order to compare different approaches to distribute tasks efficiently, a common evaluation framework is required. This ensures the quantitative compatibility of the results on the one hand and allows for the quantitative comparison of approaches on the other hand.

A framework for the measurement of the observed decision strategy performances was developed by [2]. In there, key performance indicators (KPIs) were defined and optimization functions proposed. Besides single system-specific KPIs, global measures across systems were defined. Further, a global objective function, that considers task realization strategies in regard with a collection of scenarios was presented. Since results are intended to be reproduced and to transfer benchmarks to a greater case study, the following aspects are considered for the evaluation of the global systems. Further details can be found in [2].

- The *total processing costs* as accumulated costs of the individual systems. Processing costs combine cost for the task realization of a certain task, such as processing costs, transportation costs, etc.
- The *total traffic intensity* as the systems current job capacity.
- The *total number* and *total time of waiting jobs* as the number or time of jobs waiting to be processed and being accumulated across individual system levels.
- The *total number of jobs* realized in time, as the number of jobs which were conducted in time, i.e. before a delay occurs in the global system as a result of unfinished jobs.
- The *common objective function* as the joint consideration of relevant criteria over scenarios following [13]. This includes e.g. a trade-off of the waiting time, the remaining time, processing costs, minimal transfer costs and job importance.

3. Benchmarks in Real-World Scenarios

Following the procedure model by [2], this section demonstrates a real-world case. The numbering corresponds to the phase numbering as presented.

1) Project Initiation. The printing case [14] was chosen with the intention to check the performance of the NDM in a practical simulation setting. Following the Industry 4.0 definition by [4], a typical production system consists of production machines (e.g. printer) and workpieces (e.g. raw materials that are to be processed). Within production, machines are transforming one or more input materials into one or more output products [4]. To connect the machinery, conveying belts are used, which ensure that the printing output of a former production step is transported to the machinery of the next production steps.

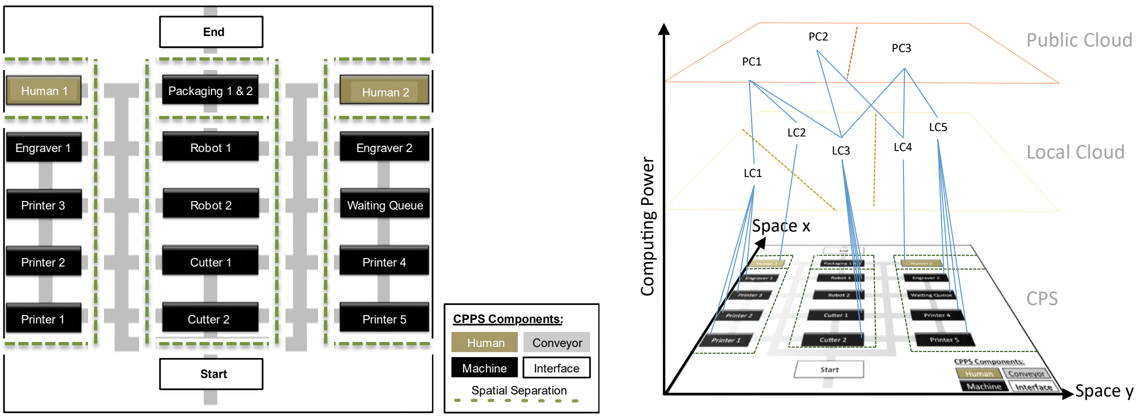
Each printer can handle different qualities, sizes and variations of paper, such that machinery and workpieces can find different production cycles through comparisons. Further, it is necessary to include parameters like speed, or variables like electricity costs, or even adapting production parameters like a changing degree of quality. It is feasible to include parameters, distinguishing between the machine agents, such as the individual computing power, the CPS specific memory, its proper sensor, actuator and communication capabilities.

2) Objectives. The general objective is to compare three different approaches, that is (1) local processing (no distribution), (2) a human-made manual task distribution approach and (3) the NDM strategy for analytical tasks. While being faced with various material flows through the CPPS, the examination of analytical task realization starts at the generation of analytical tasks at each CPS because of material-consuming production tasks. We so consider analytical tasks only and disregard the flow of materials.

3) Systems and Connections. The arrangement of the machines within the CPPS can be seen in Figure 2(a). Here, one can see machines visualized by dark rectangles and conveyors visualized by gray rectangles. While the process starting point and ending point are visualized with help of white rectangles and serve as interface for the production process entry and outlet, human workers are visualized with help of yellow rectangles. CPS are surrounded by green dashed lines, which shall represent separate rooms or buildings.

In order to consider the missing elements of analytical infrastructures (see section 2.1), Figure 2(b) visualizes the CPS within its analytical context: Above the CPS level having the lowest computing power, one can find one level for local cloud machines and one level for public cloud machines. These contain local or public cloud machines having the same computing power. The limitation to have only three levels is only for this graphical purpose. Since machines do seldomly obtain the same computing power in reality, practically, the model provides several levels of CPS, local clouds and public clouds.

In analogy to room separations visualized in green in in Figure 2(a), one can find dashed lines at the local cloud and public cloud levels as well. These rather represent collaboration spaces allowing horizontal distributions. The valid kind of vertical distribution is visualized by blue associations in Figure 2(b).



(a) Printing Center Layout. (b) Analytical Context.

Figure 2: Abstract Model of the Scenario Design

4) Scenario Collection. During the fourth phase of the procedure model, typical scenarios that impact task realizations were identified. The scenarios include the reference scenario, price increase of public clouds, power enhancement of CPSs, adding computing resources, and breakdown of system elements. During a first simulation, scenarios beside the reference have been disregarded. However, given the practical importance, they are to be considered in the future.

5) Initialization Parameter. The initialization parameters were collected in workshops with the customer. Here, system administrators, production and process owners as well as analytics experts were surveyed. Considering the scenario design of Figure 2(a) and (b), the production setting can be transferred to a computational model as follows. The scenario requires $N=15$ CPS, $M=5$ local cloud systems and $K=3$ public cloud systems. Corresponding to the underlying processes and production runs, each generates independently analytical tasks from eight task types as they have been drawn in section 2.1.

6) Transfer and Processing Strategies. Suppose we have three transfer strategies: A first transfer matrix provides a strategy called 'Do-Not-Transfer-Anything'. Using matrix structure, this looks like an identity matrix since 100% of each task type stays at its origin system.

A second transfer matrix stands for a strategy called 'Workshop-Based'. This has been conceptualized by a group of experts as the procedure model requires in phase six. Having held sessions over the period of two days with 5 experts being responsible for the analytical processing, 4 business process management experts and 4 production managers, various transfer strategies were established individually. These were discussed in groups in regard with the reference scenario selected. Finally, a joint transfer strategy was established, whose visualization can be found in Figure 3. This characterizes a good and reasonable task realization.

A third transfer matrix, coming from the 'New-Decision-Maxim' presented in section 2.2, can be found in Figure 4. Compared with Figure 3, here we cannot see a well-planned, diverse transfer strategy, which results because of the limited set of the four escalation strategies of the heuristic. It characterizes a third party focus.

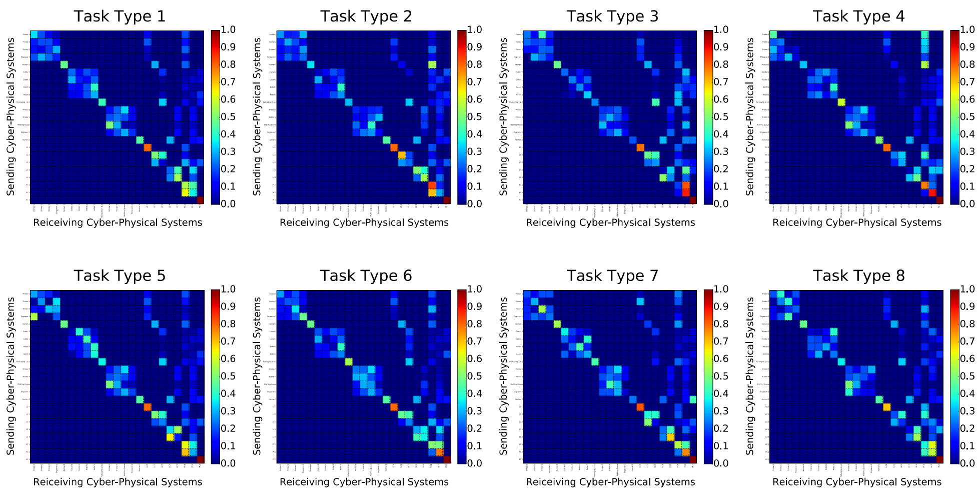


Figure 3: Workshop-Based Transfer Strategy of Printing Example

7) Simulation, Analysis and Comparisons. The initial configuration results in a workload, as can be seen in Figure 5(a). Each task type has been coloured by separate colour. Here, one can see that the traffic intensity of *Human 1*, *Robot 1*, *Printer 5* and the *Waiting Queue* exceeds the limit of *1.0*, which means that those systems are overloaded and will break down.

Since the traffic intensity shown here is not changed by transfers of the first transfer strategy ('No-Transfers-At-All'), its workload after transfers is the same and an urgent transfer is required. Focusing on the traffic intensity of all local and public clouds, one can identify a potential in free capacities. Ideally, those capacities are used for the processing of tasks exceeding local capacity.

As jobs are transferred, best task realization runs for each transfer strategy can be found in Figure 5(b-c). These have been identified by the objective function, as it was presented by [13]. Figure 5(b) shows system specific traffic intensity following a 'Workshop-Based' transfer strategy. Beginning with the processing of tasks that came in last (Last-In-First-Out-based processing strategy), one can see a significant transfer of tasks to systems having a greater computing power. So, a system overload can be avoided successfully.

Figure 5(c) shows system-specific traffic intensities after NDM-based task transfers. Beginning with the processing of tasks having the lowest remaining time (First-Remaining-In-First-Out-based processing strategy), one can identify even more tasks to be transferred to systems having a greater computing power than the 'Workshop-Based' transfer strategies demands for. Here, a system overload can be avoided successfully, too.

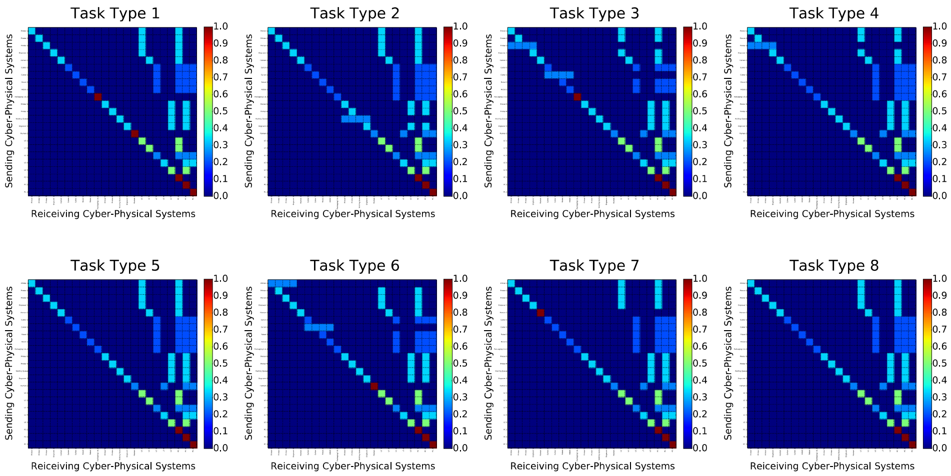
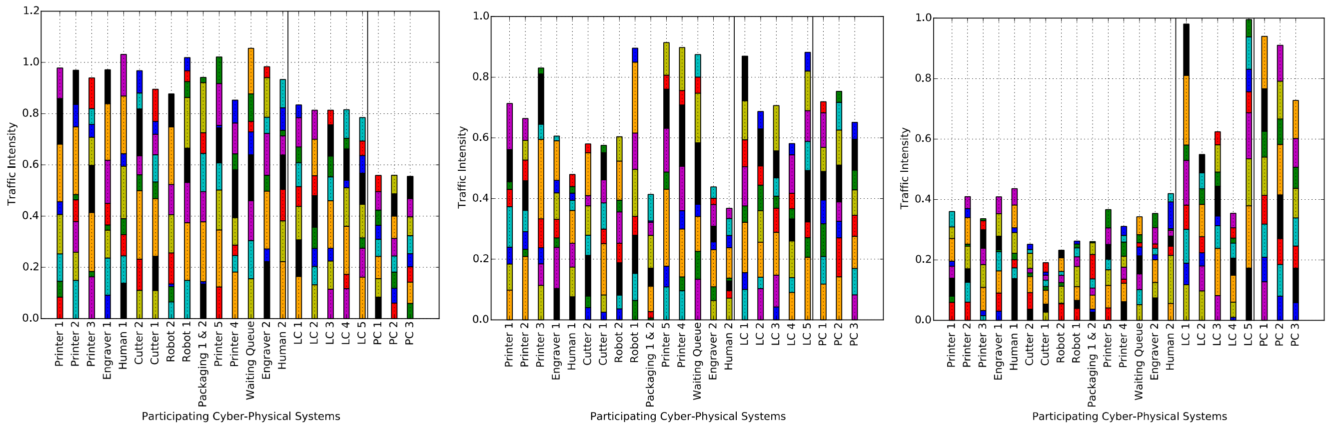


Figure 4: NDM-Based Transfer Strategy of Printing Example

8) Target Concepts. Comparing the results of the previous phase ("Simulation, Analysis and Comparison"), a change to the NDM is suggested. Here, the processing strategy shows minor importance, since all combinations of processing strategies and the new decision strategy improve the situation of the customer. A detailed evaluation can be found in the following chapter.



(a) No-Transfer-At-All - First-Remaining-In-First-Out

(b) Workshop-Based Transfers - Last-In-First-Out

(c) NDM-Based Transfers - First-Remaining-In-First-Out

Figure 5: Best Task Realization Runs of Printer Example

4. Evaluation

Having rebuilt the simulation setting and results of [2] with the aid of a Python implementation, which is deterministic, as results are reproducible by the same initial conditions, discrete, as simulation time is based on fix time points and process-oriented, as the process steps of analysing, transferring and processing have been considered, the simulation setting has been verified. Having then applied the production scenario described in section 3, the following evaluates given artefacts and creates a trade-off between various approaches. A first subsection deepens the evaluation in focusing the great printing example. Further, the common objective function [13] is verified.

4.1 Heuristic Validation

The simulation of the printing example, as it was shown in section 3, resulted in different performance levels for each transfer strategy. An overview can be seen in Table 3.

Table 3: Transfer Strategy Performance of Printing Center

Transfer Strategy	*NDM-Based Transfers*	*Workshop-Based-Transfers*	*NTAA-Based Transfers*
Total Processing Costs	127 734.8158	110 501.3583	94 368.7225
Total Traffic Intensity	0.4793	0.6828	0.8770
Total Number of Waiting Jobs	12.1521	17.7485	23.4977
Total Time of Waiting Jobs	1.5947	1.6604	1.7260
Total Job Realization in Time	{183 - 184}	{182 - 184}	{164 - 169}

Here, one can see that the most expensive, system-wide task realization is caused by transfers of the New-Decision-Maxim. Workshop-Based transfers come second and No-Transfers-At-All third.

Faced with the total number of jobs, that were realized in time, extra costs can be justified. New-Decision-Maxim-Based transfers and Workshop-Based transfers realized the most tasks in time, although Workshop-Based transfers show a higher variance. Showing *23* systems with *8* job types per system, all *184* jobs types could only be realized in time following the New-Decision-Maxim or Workshop-Based transfers. While New-Decision-Based transfers contain *183* out of *184* jobs as well, Workshop-Based transfers show *183* and *182* out of *184* jobs as well. Only *164-169* out of *184* jobs have been realized in time following the No-Transfers-At-All transfer strategy. Mostly, better results are achieved because of their transfer focus on more powerful computers. This is why further KPIs improve with better approaches, as can be seen at the decreasing number of waiting jobs and the decreasing total time of waiting jobs.

Table 4: Process Strategy Performance of Printing Center (Sorted by Total Job Realization in Time)

Transf. Strategy	**Process Strategy**	**Com. Obj. Func.**	**Total Job Remaining Time**	**Total Job Realization In Time ∨**
N-D-M	First-Remaining-In-First-Out	0.0659	31.5116	184
N-D-M	Low-Importance-In-First-Out	0.0661	31.5404	184
N-D-M	First-In-First-Out	0.0664	31.5527	184
N-D-M	Slowest-In-First-Out	0.0671	31.7414	184
W-B-T	Last-In-First-Out	0.0908	27.6806	184
W-B-T	Most-Expensive-In-First-Out	0.0914	27.7934	184
W-B-T	Slowest-In-First-Out	0.0914	27.9510	184
W-B-T	Task-Type-Ascending	0.0917	27.9663	184
N-D-M	Most-Expensive-In-First-Out	0.0673	31.6426	183
N-D-M	Task-Type-Ascending	0.0676	31.7473	183
W-B-T	Low-Importance-In-First-Out	0.0926	27.6820	182
W-B-T	First-Remaining-In-First-Out	0.0915	27.6229	183
W-B-T	High-Importance-In-First-Out	0.0916	27.7376	183
N-D-M	High-Importance-In-First-Out	0.0670	31.6086	183
N-D-M	Last-Remaining-In-First-Out	0.0668	31.5833	183
W-B-T	Last-Remaining-In-First-Out	0.0915	27.7487	183
W-B-T	First-In-First-Out	0.0913	27.6850	183
W-B-T	Task-Type-Descending	0.0898	27.4073	183

Transf. Strategy	**Process Strategy**	**Com. Obj. Func.**	**Total Job Remaining Time**	**Total Job Realization In Time ∨**
W-B-T	Cheapest-In-First-Out	0.0900	27.5762	183
W-B-T	Fastest-In-First-Out	0.0904	27.4587	182
N-D-M	Task-Type-Descending	0.0660	31.3825	183
N-D-M	Fastest-In-First-Out	0.0661	31.4111	183
N-D-M	Cheapest-In-First-Out	0.0663	31.4920	183
N-D-M	Last-In-First-Out	0.0666	31.5545	183
N-T-A-A	First-Remaining-In-First-Out	0.1248	23.5807	168
N-T-A-A	Task-Type-Descending	0.1230	23.3024	168
N-T-A-A	Cheapest-In-First-Out	0.1244	23.5164	168
N-T-A-A	Last-In-First-Out	0.1261	23.6605	167
N-T-A-A	Low-Importance-In-First-Out	0.1267	23.6904	164
N-T-A-A	Fastest-In-First-Out	0.1224	23.3521	169
N-T-A-A	First-In-First-Out	0.1257	23.7210	166
N-T-A-A	Most-Expensive-In-First-Out	0.1271	23.8776	167
N-T-A-A	Slowest-In-First-Out	0.1289	24.0453	165
N-T-A-A	Task-Type-Ascending	0.1286	24.0758	166
N-T-A-A	Last-Remaining-In-First-Out	0.1277	23.7815	164
N-T-A-A	High-Importance-In-First-Out	0.1275	23.8132	165

Considering further processing strategies, performance levels could be found as Table 4 shows. Here, task realization strategies (this includes transfer and processing strategies) are sorted by the number of task types, that were realized in time (first criteria), and the common objective function (second criteria).

As best strategies, New-Decision-Based realization strategies can be identified. Those are followed by Workshop-Based realization strategies. The middle field shows a mixture of New-Decision-Based and Workshop-Based realization strategies. Lastly, realization strategies on base of No-Transfers-At-All-Based realization strategies can be identified without exceptions.

While a concrete ranking of all task realization strategies can be found within the table, best strategies focus the remaining time, the importance and the processing costs. In Section 3, only best candidates per category have been presented in detail.

4.2 Objective Function

Focusing the printing case, Table 5 shows a ranking of task realization strategies sorted by the common objective function of [13]. Since this results in a similar order of task realization strategies as a list ordered by the total job realization in time, this is an indicator for a working objective function. A less complex scenario with less conflicting results would underline this perfectly.

As in this complex scenario, a ranking may not be trivially built on base of the number of task types, that were realized in time (first criteria) and the total job remaining time (second criteria), rather a complex trade-off of the remaining time, the importance of a task, etc. was required. One example for this kind of trade-off can be found at the objective function. Considering this specific trade-off, without exceptions, best task realization strategies build on the New-Decision-Maxim. Those are followed by the Workshop-Based task realization strategies without exception. Lastly, No-Transfer-At-All-Based strategies can be found. Since the New-Decision-Maxim considers parts of the objective function, this is not a surprising result. But this serves as indicator for a functioning of the objective function.

Table 5: Process Strategy Performance of Printing Center (Sorted by Objective Function)

Transf. Strategy	Process Strategy	Com. Obj. Func. ∧	Total Job Remaining Time	Total Job Realization In Time
N-D-M	First-Remaining-In-First-Out	0.0659	31.5116	184
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N-D-M	Fastest-In-First-Out	0.0661	31.4111	183
N-D-M	Cheapest-In-First-Out	0.0663	31.4920	183
N-D-M	First-In-First-Out	0.0664	31.5527	184
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N-D-M	Task-Type-Ascending	0.0676	31.7473	183
W-B-T	Task-Type-Descending	0.0898	27.4073	183
W-B-T	Cheapest-In-First-Out	0.0900	27.5762	183
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W-B-T	Last-In-First-Out	0.0908	27.6806	184
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N-T-A-A	Cheapest-In-First-Out	0.1244	23.5164	168
N-T-A-A	First-Remaining-In-First-Out	0.1248	23.5807	168
N-T-A-A	First-In-First-Out	0.1257	23.7210	166
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N-T-A-A	Low-Importance-In-First-Out	0.1267	23.6904	164
N-T-A-A	Most-Expensive-In-First-Out	0.1271	23.8776	167
N-T-A-A	High-Importance-In-First-Out	0.1275	23.8132	165
N-T-A-A	Last-Remaining-In-First-Out	0.1277	23.7815	164
N-T-A-A	Task-Type-Ascending	0.1286	24.0758	166
N-T-A-A	Slowest-In-First-Out	0.1289	24.0453	165

5. Conclusion

5.1 Summary

The paper starts with an overview of different important aspects of Industry 4.0 and research that is relevant analytical infrastructures. The combination of the different aspects has resulted in a mathematical model by [2], which builds the basis for the experimentation of a real-world case study presented in this contribution. We provide a first real-world case study, that benchmarks common task realization strategies. These consist of (1) different transfer (distribution) and (2) processing strategies. As such, we contribute to validate the common objective function of [13], that has been applied to a small, theoretical example so far. The results highlight the importance of distribution and task prioritization in networked production infrastructures.

The research question (*How can analytical tasks be efficiently be distributed and processed within networked production infrastructures?*) can be answered by the selection of the most promising task realization strategy and infrastructure design. The real-world case study demonstrates the strengths of heuristic approaches and is in accordance with results of [2]. This includes the perspective of common KPIs and the common objective function of [15]. Considering the objective function as optimization criteria, with this, the AI-based task transfers within the networking infrastructure is prepared.

5.2 Limitations and Outlook

Even though modern analytical infrastructures as well as production settings have been evaluated carefully, individual setups, especially cross-company combinations with multiple sites [15], might not match the structure of this model. Even though the model allows for the modification of arbitrary many and complex levels, insights were derived with three hierarchy levels (Figure 2). For the sake of demonstration simplification was needed. Future research should incorporate more complex and multi-site setups.

Regarding the proposed NDM, further case studies, incl. sensitivity analyses, should be employed to allow for generalization of the results and further increase the current level of validity. The extension beyond the Analytics context allows to apply the results in related domains. Finally, dynamics in distributed infrastructures should be incorporated in the simulation, as these are proposed by disregarded scenarios.

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